ENCODING DIFFERENCES IN AGING ADULTS CAN EXPLAIN ASSOCIATIVE MEMORY DEFICITS

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ENCODING DIFFERENCES IN AGING ADULTS CAN EXPLAIN ASSOCIATIVE MEMORY DEFICITS

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ABSTRACT

The relationship between aging and associative memory decline has been well-established in literature, however there is no clear reasoning for this decline. Recent functional magnetic resonance imaging (fMRI) studies have shown that aging adults show decreased neural specificity across the cortex, now commonly termed dedifferentiation. The current research attempts to find a relationship between increased dedifferentiation with age and their resulting decreases in associative memory performance. By utilizing multi-voxel pattern analysis (MVPA) classifiers, the level of neural distinctiveness of the variably aged adults can be quantified and compared to associative memory performance. We found that neural distinctiveness was decreased with age as well as retrieval of increasing levels of specificity of associate items. This suggests that the associative memory decline in older adults can be explained by a decrease in neural specificity for the specifics of associate items during encoding.

INTRODUCTION

Healthy aging is accompanied by various neural changes that lead to age-related cognitive decline. This decline is most notable in episodic memory tasks, especially associative memory tasks. Associative memory is the ability to learn and remember relationships between different items like words, faces, and scenes. As memory for associated pairs declines with age, memory for individual items remains intact (Saverino et al., 2016), a phenomenon termed the associative deficit hypothesis (Naveh-Benjamin, 2000). One theory behind the advancement of this problem with age has been a generalized decrease in neural selectivity known as dedifferentiation. Neural dedifferentiation is defined as increased similarity in neural activation patterns for unrelated and highly distinct items and decreased similarity in neural activation patterns for related or overlapping items (Carp et al., 2011a). Dedifferentiation is most commonly studied for visual stimuli (Park et al.,2004; Goh, Suzuki & Park, 2010; Carp et al., 2011a; Voss et al., 2008). However, it has also been found within the motor control network (Carp et al., 2011b) suggesting that this reduction in neural specificity is more general across the aging brain as opposed to restricted to certain brain networks.

In order to compensate for the diminished neural selectivity, older adults have shown bilateral activation for tasks that younger adults only elicit unilateral activation (Cabeza et al., 2002). However, even with this compensatory activity, older adults still show underlying differences with encoding and retrieval mechanisms that inhibit their performance from equating that of younger adults. Two different factors have been suggested for contributing to age-related memory impairment: reduced formation and availability of detailed stimulus representations that could be used to disambiguate between similar and highly overlapping stimuli and a reduced ability to access and retrieve these detailed representations in a goal-directed manner (Trelle et al., 2017). Research differentiating recollection and familiarity pathways shows a reduction in the recruitment of lateral prefrontal regions associated with goal-directed recollection in older adults (Trelle, Henson & Simons, 2019). This corroborates the finding that older adults have intact item memory as they can rely on familiarity-based recognition, however, in doing so with associative memory tasks would lead to decreased task performance (Yonelinas, 2002). Problems with initial encoding efficacy have also been found as older adults tend to only encode the general conceptual ‘gist’ of study and test items as opposed to younger adults who process more robust details about the items (Koutstaal & Schacter, 1997). Additionally, Goh, Suzuki and Park (2010) demonstrate that dedifferentiation applies to within-category stimuli, such that younger adults process and encode more distinctive representations for individual stimuli items than older adults do. A decrease in neural adaptation to individual stimuli with age would result in the brain being unable to differentiate between, for example, one face from another hindering their associative memory performance for these faces. Finally, even if older adults formed high fidelity neural representations, they have still been shown to lose specificity in long-term memory upon retrieval (St-Laurent et al., 2014). Being able to conceptualize this decrease in neural specificity within older adult’s neural representations of associative stimuli using fMRI can help illuminate its importance in the associative deficit problem.

Dedifferentiation has been shown most explicitly in regions associated with direct stimulus type relationships including the fusiform face area (FFA) and parahippocampal place are (PPA), which are selective to faces and scenes respectively (Kanwisher, McDermott & Chun, 1997; Dilks et al., 2013). Within these regions, it has been shown that different categories of their responsive stimuli elicit specific neural signatures that can be used to distinguish the specificity of representations made during encoding. This means that different male and female faces elicit unique neural signatures that can be differentiated using fMRI analysis (Kriegeskorte et al., 2007). Multi-voxel pattern analysis (MVPA) uses the dissimilarity between these neural signatures found in fMRI voxels to make inferences about the current brain state in respect to each varying stimulus. Due to dedifferentiation with age, older adults have more similarity between these specific neural signatures making it harder for MVPA classifiers to identity the correct associate stimulus that elicited that neural signature. In addition, it also relates to decreased associative memory performance as the specifics of the associative image are not available within the neural representation for the older participant to tell similar but different stimuli apart. Collectively, this reduced selectivity of neural representations in older adults during associative encoding and its relationship with MVPA brain state predictability and subsequent memory for associative pairs supports the idea that age- related dedifferentiation is critical in the progression of the associative deficit.

In the current study, we are investigating this relationship between neural specificity within the FFA and PPA and later memory retrieval for associated face and scene images with respect to age. Within our associated pairs we had two different types of face and scene images: male and female, and indoor and outdoor. Within each of these subcategories, we had four different images meaning that the participants had to make a conscious decision about the correct associate image forcing them to rely on recall as opposed to familiarity-based reasoning. The neural representations that each of these stimuli types elicited were fed into a MVPA classifier that then used these representations to make a layout of what face and scene neural activity looks like. This information allowed the classifier to predict from individual subject neural activity what stimulus associate they were encoding. In agreement with the dedifferentiation hypothesis, we hypothesize that increased age should show decreased MVPA classifier accuracy performance because of the decreased specificity of older adult's neural representations for distinct stimuli types. This decrease in MVPA classifier performance should be predictive of decreased associative memory performance with age.

METHODS

I. Participants

The participants of this study were 23 young adults (ages 18-35; 12 males) and 18 older adults (ages 65-73; 8 males). Younger and older adults had a similar amount of education [$t(39) = .415$, $p = .680$]. The group descriptive statistics are presented in Table 1. A total of five additional older adults and two additional younger adults were excluded from the study due to claustrophobia and excessive movement in the scanner, and inappropriate responding during the retrieval task. All participants were recruited from the Georgia Institute of Technology and the surrounding Atlanta area. All participants were right-handed, proficient English speakers, with normal or corrected to normal vision (MRI- compatible glasses were used when necessary). All participants were screened for both medical implications and fMRI safety implications. Participants were excluded if they showed reports of psychiatric/neurological disorders, vascular disease, or psychoactive drug use. Additionally, participants were excluded if they contained any safety hazards for the fMRI including if they were pregnant, claustrophobic, had any implanted ferromagnetic materials or devices that might cause issues within the scanner. All participants were compensated with either class credit or $10 per hour and signed consent forms that were approved by the Georgia Institute of Technology Review Board.

Measure	Young (n = 23)	Older (n = 18)
Age	24.13 (5.15)	68.72 (4.00)
Sex	12 males	8 males
Education	16.09 (2.37)	16.39 (2.23)
MoCA	N/A	27.83 (1.62)

Note: Standard deviations in parentheses.

Table 1: Group Descriptive Statistics

II. Materials

A total of five hundred and twelve color images of differing nameable objects taken from Hemera Technologies Photo-Objects DVDs, or from the Internet via Google, were used. All images were displayed on a black background. None of the object images contained the same object. In addition, eight images of faces (four male and four female) and eight images of scenes (four indoor and four outdoor) were used as additional stimuli for the experiment. The faces were taken from the Max Panck Institute's FACES database (Ebner, Riediger, & Lindenberger, 2010) and the scenes were taken from the SUN database (Xiao, Hays, Ehinger, Oliva, & Torralba, 2010).

III. Procedure

The study was divided into two phases: encoding and retrieval. Practice sessions were administered before the start of both phases so that the participant was well versed on the tasks. The encoding phase was broken up into four blocks. All four blocks were scanned and the stimuli within each block were counterbalanced so that each stimulus was paired with a different cue type across participants. The retrieval phase contained eight blocks consisting of stimuli from the encoding phase as well as new stimuli. There was a total of 256 images studied in the encoding phase; all of which were later tested in retrieval with the addition of 256 new images for a total of 512 images presented in retrieval. The experimental design is shown in Figures 1 and 2. The encoding task lasted 52 minutes and the retrieval task 90 minutes. The entire experiment lasted around 3 hours with completion of paperwork and transition into and out of the fMRI scanner.

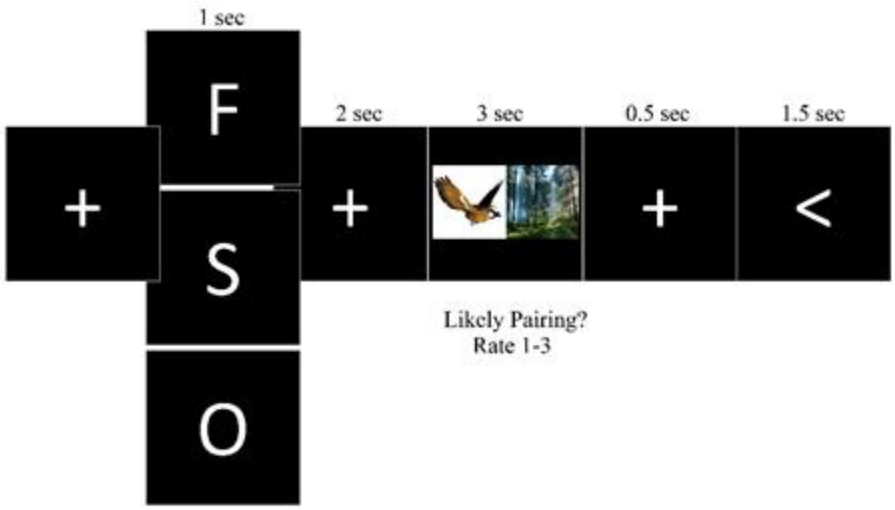

Figure 1: Encoding Task Experimental Design

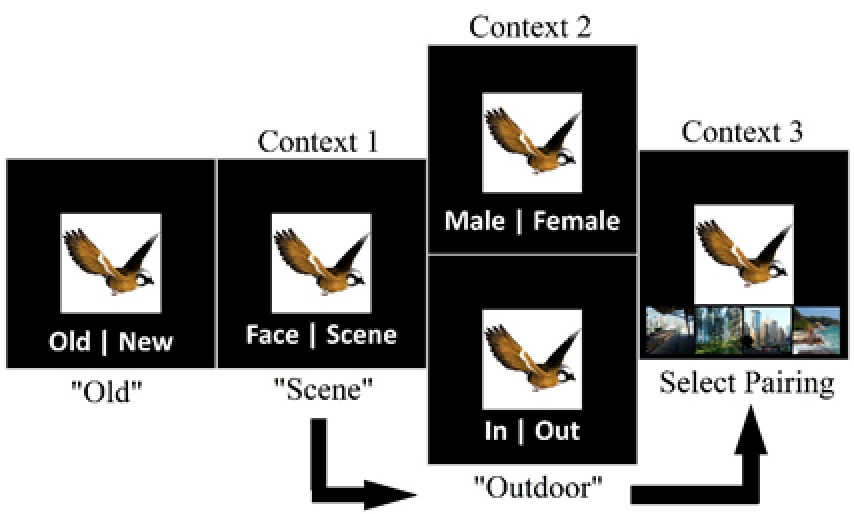

Figure 2: Retrieval Task Experimental Design

a. Encoding

Participants were presented with 64 stimuli in each block for a total of 256 stimuli in all four blocks. For each trial, the participant was first presented with a fixation cross in the middle of the screen that prompted them that the trial was about to begin. Following this, a letter cue was shown for one second. The cue was either informative of what type of image (either a face or a scene) was going to be paired with the object or it was neutral and did not give any information about the image that the object was going to be paired with. For example, if the participant was going to see the object paired with a face image, then the informative cue of F would have been shown. The informative cue for a scene image was an S and the neutral cue letter was an O. There was also the addition of catch trials which would consist of the participant being presented a cue but no stimulus to follow. After the catch trial, the participants would continue onto the arrows task described below.

Following the cue, another fixation cross was presented on the screen for two seconds. Then, an image of an object was presented next to either a face or a scene and displayed for 3 seconds as shown in figure 1. While these images were on the screen, the participants were asked to rate how likely the pairing of the two images are. The participants were asked to respond with their rating using a button box: "1" if it is not a likely pairing, "2" if it is a somewhat likely pairing, and "3" if it is a likely pairing.

Each trial was then followed by a fixation cross lasting 500 ms and then an arrows task. The arrows task is used to maximize design efficiency by pseudorandomly interspersing event trials with "active" baseline trials lasting between 1.5 and 6 s, jittering in increments of 1.5 s (Dale, 1999). Every 1.5 s, an arrow appeared on the screen and the participants were instructed to use the button box to respond to what direction the arrow was pointed: "1" if the arrow pointed to the left and "2" if the arrow pointed to the right. The purpose behind this task was to keep the participant engaged and to minimize default mode network activity (Stark & Squire, 2001). There was a total of either 1-4 arrows in the arrows task.

Each block in the encoding phase lasted 13 minutes with the whole phase lasting 52 minutes. Immediately following the completion of the encoding task, the participants were removed from the scanner and went back to the lab room to complete an fMRI questionnaire, as described below, and for older adults a neuropsychological assessment before the start of the retrieval task.

b. Neuropsychological Assessment

After completion of the encoding phase, older participants were administered the Montreal Cognitive Assessment (MoCA) to rule out any cognitive impairments, such as mild cognitive impairment. A score of less than 26 out of 30 for the MoCA is the traditional cutoff for normal memory performance, however, the MoCA has been found to not fairly assess the cognitive status of people from differing educational, cultural, and racial backgrounds (Carson, Leach, & Murphy, 2018; Manly, 2005; Sink et al., 2015). Due to this, any participant that scored below a 26 and scored within two standard deviations of mean performance were not excluded from the analysis. Average MoCA scores for the older adults are presented in Table 1.

c. Retrieval

After completion of the neuropsychological assessment, the participants began the practice retrieval task. Participants completed a practice retrieval phase until accurately understanding the task before moving onto the retrieval task. The retrieval task consisted of eight blocks lasting around a total of 90 minutes. Participants were tested on all 256 images that were presented to them in the four encoding blocks in addition to 256 new images that were not in the encoding task.

The retrieval task began with the presentation of the object image in the center of the screen with the choices “old” and “new” displayed underneath. Selecting the choice “old” would denote that the image was presented in the encoding phase and selecting the choice “new” meaning that the image was not presented in the encoding phase. Participants could answer here for up to 7 seconds. If the participant thought that the image was new, then they would directly advance to the next object image. If the participant thought the image was old and was therefore one they had seen before in the encoding phase, then the next screen would ask if that object was paired with a face or scene in encoding. If the participant thought that the image was old but it was really a new image, they would continue on like it was an old image.

After signifying if it was a face or scene image paired with that object image, they were brought to the subsequent question based on their selection. If the participant said that the object image was paired with a face, then the next screen would ask if it was a male or female face that it was paired with. If the participant said that the object image was paired with a scene, then the next screen would ask if it was an indoor or outdoor scene that it was paired with.

Following this selection, they were brought to the final screen in which they were shown all four of the possible scenes or faces that it could have been paired with depending on the selections that they made prior. Here they would have the options of pressing “1”- “4” on the keypad to select the correct image. Participants who answered incorrectly at any of these steps were still prompted with the next question and continued making selections based on what they thought they remembered, making the participants unaware of their accuracy of the task. If at any point the participant did not know the answer to the question, then there was a button press denoted as ‘I don’t know”. If they said at any time that they did not know the answer, then they would be brought to the next object image. The specific prompt questions were shown for a total of 5 seconds to allow for responses. After deciding on the final image that was paired with the object image, participants would continue straight into the next object image.

Each trial was pseudorandomized so that there was an equal spacing of informative cue and neutral cue trials. The blocks were additionally randomized so that there was an equal number of old and new images throughout all eight blocks. After completion of the retrieval task, participants were instructed to fill out an exit questionnaire.

d. Questionnaire

Participants were asked to complete two debriefing questionnaires following scanning and completion of the experiment. These assessed their level of fatigue, understanding of the tasks, and general thoughts about any strategies they used to complete the tasks. These data are not presented here.

IV. fMRI Analyses

a. Preprocessing

Scanning was performed on a 3T Siemens TIM Trio system at the Center for Advanced Brain Imaging. Functional data was acquired using a gradient echo pulse sequence (37 transverse slices oriented along the anterior-posterior commissural axis with a 90-degree upward tilt to avoid the eyes, repetition time of 2 s, echo time of 30 ms, 3×3×3 mm voxels, 0.8 mm interslice gap). Four encoding blocks of 366 volumes were acquired. The first 2 volumes of each block were discarded to allow for equilibration effects. A high-resolution T1- weighted magnetization-prepared rapid acquisition gradient echo (MPRAGE) image was collected for normalization.

b. Statistical Analysis

Data were preprocessed and analyzed via SPM12 (SPM12, http://www.fil.ion.ucl.ac.uk/spm/software/spm12/). Images were corrected for differences in slice timing acquisition using the middle slice of each volume as the reference, spatially realigned and resliced with respect to the first volume of the first block. Each participant's MPRAGE scan was co-registered to the mean EPI image, produced from spatial realignment. Each co-registered structural scan was then segmented using the Diffeomorphic Anatomical

Registration Through Exponentiated Lie algebra (DARTEL) SPM 12 toolbox (Ashburner, 2007). DARTEL is a suite of tools fully integrated with SPM 12, which the SPM 12 manual recommends over optimized normalization, to achieve sharper nonlinear registration, for inter-subject alignment. Normalized EPI images were written to 3 × 3 × 3 mm and smoothed with an 8 mm full-width at half-maximum isotropic Gaussian kernel. The EPI data was then high-pass filtered to a minimum of 1/128 Hz and grand mean scaled to 100.

c. Multivariate Pattern Analyses

The goal of our classification analysis was to target robust sensitivity to perceptual specific category-level information (male versus female faces and indoor versus outdoor scenes). Two classifiers were used to do this: one targeting specific face categories versus a general scene category (male versus female versus scene). The other targeting specific scene categories versus a general face category (indoor versus outdoor versus face). We chose to use two classifiers in the 3-way analysis fashion in order to eliminate any potential bias within the classifiers.

Comparing the two specific categories to the other general category forced the classifier to make a decision about the specific stimuli trials and allowed there to be another category the classifier could pick when the trial didn't align with either of the specific category classifications. These analyses were based on penalized logistic regression using L2-norm regularization as depicted in the LIBLINEAR classification library (http://www.csie.ntu.edu.tw/~cjlin/liblinear/).

Classification was conducted for 10 seconds following the presentation of the cue, thus consisting of the five TRs following the cue onset. The TRs were weighted as [0 0 0.25 0.5 0.25] in order to accurately model the hemodynamic response function. This weighting scheme was also utilized in order to only capture the data from the current stimulus presentation and not the following stimulus presentation.

Both classifiers were trained to discriminate between categories of an image. Thus, training data was grouped by the category of the currently encoded image. For the face specific classifier, trials were grouped to be a female face, a male face and a scene. For the scene specific classifier, trials were grouped to be an indoor scene, an outdoor scene or a face. Catch trials were not included in the classification analysis, only trials in which a stimulus followed a cue were included. A 3-fold cross validation was used for classification analyses for both classifiers such that for the four blocks in encoding, three of the blocks were used for training and the other block was used for testing. This was repeated until all four encoding blocks were used in both training and testing. A penalty parameter of 1 was used for both of these classification analyses. Further data preprocessing was done by the Princeton MVPA Toolbox (http://www.pni.princeton.edu/mvpa/) and custom Matlab scripts.

A bilateral anatomical mask from the AAL atlas was used for both classification analyses. This mask included the fusiform gyrus and the parahippocampal gyrus. These regions were selected due to their differential sensitivity to faces and scenes. Additionally, constricting our search to these regions lowers the number of voxels in analysis which has been found to improve classification performance. In total, the mask consisted of 1086 voxels. This number of voxels was additionally slimmed by using a non-peaking feature selection that only selected the top 750 voxels in the training set. The top 750 were selected using an ANOVA which identified the voxels within the training set with the maximal discrimination between categories. This specific number of voxels was utilized because this amount maximized classifier performance for a face versus scene classifier during the training and testing of the encoding set while minimizing the number of features taken into classification analysis, as seen in **Figure 3**.

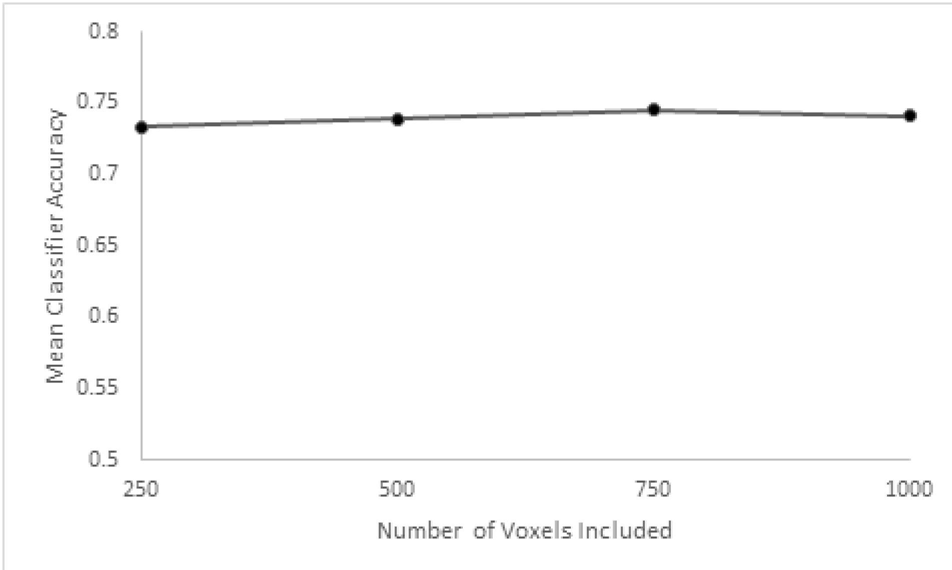

Figure 3: Mean classification accuracy for all encoding trials as a function of the number of voxels included

The use of 3-way classifiers allows us to get the most accurate classification of the different stimulus types. The classifier determines how much evidence there is for each stimulus type per trial and classifies it as the stimulus type that has the most evidence. Each trial in the testing set is recorded as either correct or incorrect based on whether the classifier's chosen category corresponds with to the actual category of the image. The classifier reports evidence for each category irrespective of the other categories. For example, a trial in the face specific category may have an evidence value of 0.20 for the female face category, 0.30 for the male face category and 0.05 for the scene category. Because the male face category has the strongest evidence, the classifier will choose that category. Given our interest in targeting perceptual specific category-level information, not general category-level information, classifier accuracy and evidence will be reported for male, female, indoor, and outdoor stimulus types only.

Classifier accuracy was computed as the percentage of trials the classifier correctly identified. Classifier evidence was the reported probability estimate for each stimulus category. This value was presented as a percentage with a range of 0 to 100 for clearer presentation. For both classifier accuracy and evidence, the data was subsampled such that it was reported for each stimulus type and memory accuracy level.

RESULTS

I. Behavioral

For all behavioral analyses, significant interactions at an alpha (α) level of 0.05 were followed up with subsidiary t-tests to determine the source of the effects. Where appropriate, reported p-values were corrected using Huynh-Feldt corrections.

a. General Item Memory Accuracy

First, we generally wanted to see if there was a difference in item memory discriminability across age and associate category. We calculated item memory as the number trial hits in the retrieval task in which the participant got the item recognition correct out of all the possible old classification trials [d' = Z(Hits) – Z(False Alarms)]. To see if the item memory was associated with the associate image category, we spilt the item memory calculations by respective image category: Male, Female, Indoor, and Outdoor. The results are presented in **Figure 4.**

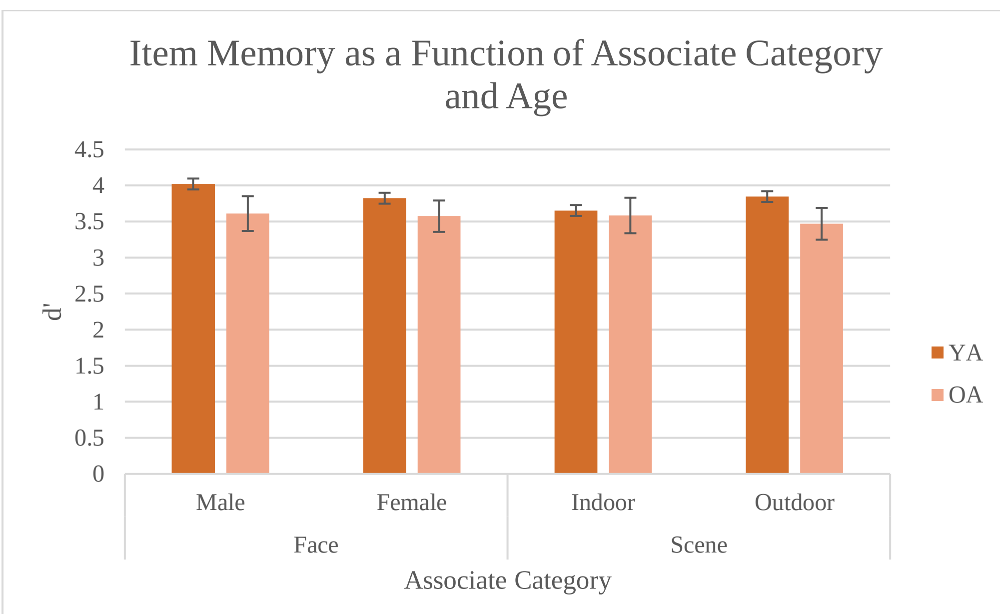

Figure 4: The mean percentage of correct responses for item memory separated by associate category, for young and older adults.

A 4 category (Male, Female, Indoor, Outdoor) X 2 age (Young, Old) ANOVA on these percentages revealed, as expected, no main effect of age or item associate on item memory [$F(3,38)$'s > 0.710, p's > 0.225].

b. Associate Memory Accuracy per Level of Specificity

In addition to item memory, we also wanted to see how associative memory was affected by age. Associative memory was calculated per level of question specificity correctly recalled in retrieval. Within the retrieval task, there were three different questions each asking more specific details about the associate image paired with the item. The level of specificity associated with item memory asked participants to discriminate if the item image was old or new and is termed s0. The next three levels of specificity were related to the specific detail of the associate image. The level of specificity that asked participants to discriminate face and scene is termed s1, to discriminate male or female and indoor or outdoor is termed s2, and finally to identify the correct associate image paired with the item image is termed s3. The associate memory accuracy for each of these levels of specificity was calculated based on the number of trials that that level of specificity was the highest level correctly answered. For example, if the item was paired with an indoor scene, and the participant answered old, then scene, then outdoor, that trial would be counted in the s1 level because that is the highest level of specificity that the participant got correct for that trial. In order to increase power and detect the effect of age, we collapsed across face and scene associate image category in the subsequent analyses. The average percent correct trials by specificity level are displayed across associate type trials in **Figure 5.**

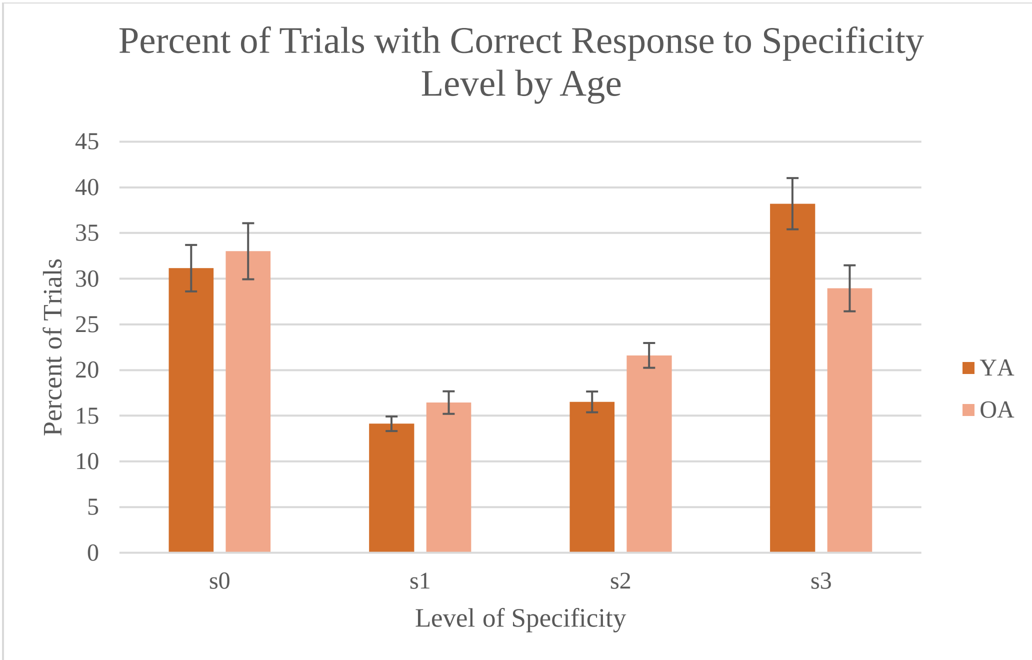

Figure 5: Percent of total trials younger and older adults got correct per specificity level.

A 4 memory (s0, s1, s2, s3) X age (young, old) ANOVA for percent correct trials revealed a main effect by category [$F(3, 38) = 21.530$, $p < 0.0001$, $\eta 2p = 0.356$]. There was no main effect of age nor a category by age interaction [$F(3,38)$'s > 1.514, p's > 0.154]. A follow up paired samples t-test by memory level showed all levels of specificity are significantly different from one another [$t(40)$'s > 1.880, p's < 0.067].

II. Multivariate Pattern Analysis

We sought to understand how MVPA classifier performance varied across age for differing levels of specificity. We investigated this relationship only at encoding and later compared the results to effects seen in the behavioral analysis.

a. Perceptual Category-Level Information Classifier

Classification analyses were performed on the encoding task by training on three blocks and testing on one block using the leave-one-out method. The classifier was trained to discriminate indoor and outdoor scenes and male and female faces in the PPA and FFA. Trial by trial classifier accuracy for each of these categories was significantly greater than chance [t(40)'s > 4.083, p's < 0.0001], confirming that the classifiers are sensitive to perceptual category-level information (indoor, outdoor, male, female) at encoding. The mean values for each of these categories is displayed in **Table 2.**

Category	Percent Classifier Accuracy
Indoor	43.627 *
Outdoor	42.949 *
Male	38.583 *
Female	38.636 *

* Significantly greater than chance (33%)

Table 2: Percent classifier accuracy per category associate image compared to chance (33%)

After confirming that the classifiers were sensitive to category-level information, we then wanted to check to see if either of the classifiers had any bias in picking a certain category of associate stimuli over another. To do this, each classifiers categories were compared using a 3 Category (for the first classifier: face, indoor, outdoor (FIO); for the second classifier: scene, male, female (SMF)) X 2 age (young, old) ANOVA on percent classifier accuracy which revealed a main effect of category for the FIO classifier [$F(2, 39) = 4.837$, $p = 0.013$, $\eta 2p = 0.203$] and a main effect of category for the SMF classifier [$F(2,39) = 3.766$, $p = 0.030$, $\eta 2p = 0.088$]. A marginal effect of age was also revealed for the FIO classifier [$F(1, 40) = 3.792$, $p < 0.059$, $\eta 2p = 0.089$] as well as a main effect of age for the SMF classifier [$F(1,40) = 7.939$, $p = 0.008$, $\eta 2p = 0.169$] both revealing that younger adults show higher classifier accuracy than older adults. Follow up t-tests on the main effect of category for the FIO classifier revealed that faces (M = 39%, sd = 5%) had lower accuracy than indoor scenes (M = 44%, sd = 9.5%) [$t(38) = 4.525$, $p = 0.012$] and outdoor scenes (M = 43%, sd = 8.5%) [$t(40) = 3.811$, $p = 0.016$]. Follow up t-tests on the main effect of category for the SMF classifier revealed that scenes (M = 43%, sd = 6%) had greater accuracy than male faces (M = 38% , sd = 8.5%) [t(40) = 4.516 , p = 0.017] and female faces (M = 39% , sd = 9%) [t(40) = 4.498, p = 0.009].

b. Classifier Accuracy per Level of Specificity

In order to understand the effect of specificity level on classifier accuracy across age, we measured percent classifier accuracy for younger and older adults across increasing levels of specificity. Percent classifier accuracy was measured similarly to the above behavioral associative memory except it is based off the classifier's ability to correctly decode the participant's memory performance. In this case, when an item was paired with a female face, if the participant was able to identify that it was a face image paired with the item but then chose male, this trial would be counted as s1 for participant's memory performance because that is the highest level of specificity that the participant got correct for that trial. If the classifier was also able to decode this brain state accurately and pile it into the s1 category, then this counted as a correct trial for classifier accuracy. The average percent correct trials by specificity level are displayed in **Figure 6.**

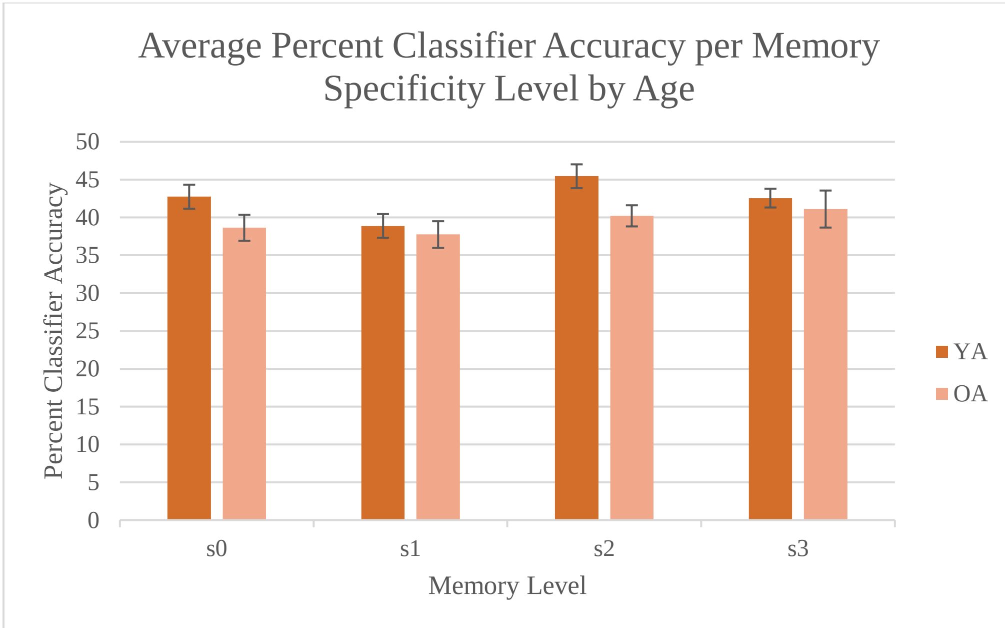

Figure 6: Average percent classifier accuracy of young and older adults across specificity level.

A 4 memory (s0, s1, s2, s3) X 2 age (young, old) ANOVA of percent classifier accuracy revealed the specific effect of memory level on classifier performance. The main effect of memory [$F(3,38) = 2.679$, $p = 0.050$, $\eta 2p = 0.064$] was consistent with the previous ANOVA across face and scene categories. Follow up paired sample t-tests revealed face or scene discrimination (s1) classifier accuracy was significantly lower than both male or female and indoor or outdoor discrimination (s2) classifier accuracy [$t(40) = 3.220$, $p = 0.003$] and individual associate discrimination (s3) classifier accuracy [$t(40) = 2.138$, $p = 0.039$]. There was no significant difference between item memory (s0) and any other memory level discrimination [$t(40)$'s < 1.443, p's > 0.157] nor a significant difference between male or female and indoor or outdoor discrimination (s2) and individual associate discrimination (s3) [$t(40) = 0.788$, $p = 0.436$]. As expected, there was also a main effect of age [$F(1,40) = 6.502$, $p = 0.015$, $\eta 2p = 0.143$], as seen in figure 8, that younger adults have overall greater classifier performance than older adults across all specificity levels. There was no significant interaction between memory and age [$F(3,38) = 0.716$, $p = 0.544$, $\eta 2p = 0.018$].

DISCUSSION

I. Behavioral results

Consistent with previous research (Saverino et al., 2016), we first exhibited that item memory does not decay with age as seen in figure 4. It can also be seen that item memory does not have a preference for any type of associate category or subcategory. Considering this, we moved on to investigate how age affects memory of associate items. In corroboration with the dedifferentiation hypothesis, we concluded that there would be an effect of age on retrieval accuracy for associate item details. As can be seen from figure 5, younger adults are able to get individual exemplar level (s3) questions correct more often than older adults. In addition to this, there is a switched relationship for the male or female and indoor or outdoor classification (s2) as it seems older adults show increased correct trial counts for this specificity level than do younger adults. This switched relationship can be due to the fact that older adults do reach the male or female and indoor or outdoor classification level but they more often than not surpass this level to get the individual exemplar correct, hence their increased correct trial count for the more specific level. Older adults are not getting the highest specificity level correct more often hence their increased male or female and indoor or outdoor memory performance exceeding that of the younger adults. Although these results are consistent with the associative deficit hypothesis (Naveh-Benjamin, 2000), their analyses did not have enough power to statistically show this effect.

What was significantly revealed, however, was the pattern of associative memory performance across different levels of specificity. In figure 5, it is shown that overall, there is higher correct trial counts for the item memory specificity level (s0) and for the most specific associate level asking to identify the individual associate image (s3) across both age groups. It can be suggested then that participants of both age groups either recall the item in order to get the item memory level (s0) correct and nothing else or they know every detail of the associate item and can get the final level of specificity (s3) correct.

II. Multivariate Pattern Analysis Results

The aim of including MVPA analysis was to understand how brain activity in the FFA and PPA when encoding associate faces and scenes would vary across age and in turn relate to the overall associative memory deficit with aging. The idea was to be able to train a classifier that was susceptible to indoor and outdoor scenes and male and female faces to decode the neural brain states of these variably aged participants and relate this classifier's performance to their actual memory performance during retrieval. As seen from table 2, we were able to create two different classifiers, one selective for general faces and specific indoor and outdoor scene neural traces and the other selective to general scene and specific male and female face neural traces. The combination of these two classifiers gave us a classification of neural traces for all specific male, female, indoor, and outdoor associates. The results, displayed in table 2, show that the classifiers were in fact selective to these different neural traces, and above chance, were able to discriminate the neural traces of the variably aged participants. This corroborates the finding that MVPA classifiers can detect differences in subcategories of information (Kriegeskorte et al., 2008)

With confirmation that the classifiers were selective to what they trained and tested on, we next needed to make sure that these classifiers did not show any bias in categorizing the different neural traces across the different associate subcategories. Across age, the two classifiers both showed increased percent classifier accuracy for scenes than they did for faces. This increased scene classifier accuracy allows us to conclude that for some trials, the classifier called a face a scene. This bias was corrected for by balancing the number of face and scene trials within the training and test data and reduced by combining the two classifiers in order to have classification of only the specific subcategories of the face and scene trials (male, female, indoor and outdoor).

In addition to this effect of associate category on classifier performance, there was also a main effect of age on the classifier performance. Across all associate item subcategories, older adults had significantly lower classifier accuracy than younger adults. This overall decreased classifier performance can be due to older adults not having as distinct neural representations as younger adults, making it harder for the classifier to accurately differentiate between these brain states for classification. This is consistent with dedifferentiation and reduced neural specificity with aging (Carp et al., 2011a). The finding that as specificity increased, classifier performance decreased was seen for both younger and older adults, however older adults showed more reduced differentiation than younger adults, confirming our hypothesis. These findings are consistent with Park et al. (2004) who also showed that regions within the FFA and PPA (the regions we isolated for classifier analysis) become less selective for their specific responsive stimuli with age. Overall, the better the brain is at separating the pattern of activity associated with processing different faces and scenes, the more specific a person's memory should be for those faces and scenes. This increased neural dedifferentiation found in older adults can contribute to their associative memory impairment.

When looking at classifier accuracy between the different levels of specificity across age, we found that classification performance was highest for the male or female and indoor or outdoor classification level (s2) (Figure 6). This is expected because the classifiers were trained to identify the differences in neural activity of these subcategories. There was also a significant difference in classifier accuracy between the face or scene level (s1) and the individual associate level (s3). Since there was no significant difference between the male or female and indoor or outdoor level (s2) and the individual associate level (s3), we can assume that the classification accuracy for these two specificity discriminations levels off at the specific subcategory level. This would make sense then for the face and scene level to be different than both the male or female and indoor or outdoor level and the specific associate level because the classifier is trained on these specific subcategory differences.

What is surprising is that there is no difference between the item memory discrimination level (s0) and any of the other specificity levels especially the specific associate subcategory (s2) level. This shows that the classifier can decipher the brain states of trials where only the item memory is correct with similar accuracy as it can decipher brain states of trials where the specific associate subcategory is correct, even though it was trained to distinguish this specific associate subcategory. There is a clear numerical difference between the classifier accuracy between these two levels, but this difference is not significant. This could be due to a reduction in power caused by the relatively small sample size that may have a negative effect on our sensitivity to detect these specificity level differences.

III. Conclusion

The present study adds to the growing body of literature consistent with the finding of neural dedifferentiation with age in associative memory tasks. In the current study, older adults consistently showed decreased memory performance during retrieval across specificity level as well as decreased classifier performance across specificity level. Combining these findings allows for confirmation of the hypothesis that reduced neural specificity of neural traces during encoding of associate items causes reduced classifier performance as well as decreased associative memory performance.

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